You're a wizard, Ari: Bias due to rewards in binary decision-making

Elise Jurasovic

A report submitted as a partial requirement for the degree of Bachelor of Science

with Honours in Psychology at the University of Tasmania, 2019

Division of Psychology, School of Medicine

University of Tasmania

Statement of Sources

I declare that this report is my own original work and that contributions of others have been duly acknowledged.

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Elise Jurasovic

October 17, 2019

Acknowledgements

I would like to thank Professor Andrew Heathcote for his supervision of this project and his guidance throughout my Honours year. I have really valued the experience of working alongside and learning from you. I would also like to thank Doctor Jim Sauer for his support throughout the course of this project.

Thank you to Matthew Gretton for developing the software used to run this experiment. Your patience and time allocated to this project have been greatly appreciated.

Thank you to all the participants who were involved in piloting, refining and final testing for this project, without whom science cannot progress – thank you!

Finally, thank you to my family, friends, and wonderful partner who have been generous with their time and resources to support me to be healthy and happy, and to achieve my best.

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Elise Jurasovic

Word count: 9606

Division of Psychology, School of Medicine

University of Tasmania

Abstract

We investigated the effect of the factors Reward Type (points vs. money) and Reward Schedule (constant vs. variable) on bias in a computerised binary decision-making task. Participants (19 female; N = 32) were aged 18 to 41 years were asked to identify which colour was in majority in a two-colour visual discrimination task embedded in a computer game. We measured reaction times, accuracy and proportion of bias congruent responses as manifestations of bias in participants' decision-making. An exact binomial test indicated that participants chose the option providing on average larger rewards at a rate greater than chance ($p < .001$). However linear mixed modelling and model selection provided minimal evidence to indicate that this bias was due to either Reward Type or Reward Schedule. Bias was greater when participants were told a priori about the likelihood of trial occurrences compared to being rewarded for correct trials ($p < .001$). Future research may test the effect of different reward sizes and true vs. random scoring on bias in the current context. In keeping with the scientific principles of honesty and collaboration, all analysis scripts, raw data, preliminary study plans and final manuscript are available online at the Open Science Framework website.

Decision outcomes are malleable and can be influenced by a range of factors including rewards, punishments, and prior information (Tversky & Kahneman, 1974). Decisions are often made using heuristics, also known as cognitive shortcuts or biases, to make best use of limited time and computational power available when making decisions (Neth & Gigerenzer, 2015). Laypeople generally consider bias to be an objectively maladaptive cognitive shortcut wherein decision outcomes do not align with facts about reality. However, biased thoughts are often adaptive, such as when one option yields a greater payoff than another, or when relying on a heuristic instead of an exhaustive algorithm when full information is not available (Haselton, Nettle, & Murray, 2015).

The use of bias as a heuristic is especially relevant given that resources such as time and computational power are always limited in real-world scenarios. Bias can be most accurately understood as a systematic pattern of thought which reduces cognitive load by extrapolating previous data and applying it to current situations (Gilovich, Griffin, & Kahneman, 2002). Understanding the drivers of bias in decision-making can inform the mechanics of cognition, contributing information to models of human cognition and neural function (Heekeren, Marrett, Bandettini, & Ungerleider, 2004).

In the current research, we attempted to understand how bias in decision-making would change when different rewards were provided for correct responses. We compared bias levels due to real vs. nominal rewards (i.e., money vs. points) and constant vs. variable reward schedules to investigate how the salience and utility of rewards would alter bias in decision-making (Zink, Pagnoni, Martin-Skurski, Chappelow, and Berns, 2004). We expected monetary rewards increase both salience and utility of rewards compared to virtual points, and we expected variable reward schedules to increase only reward salience as compared to constant reward schedules. To encourage use of cognitive biases, we limited the time and information available for each decision to be made. Participants were asked to indicate which colour was in majority in a two-colour stimulus, with one colour rewarded more highly than the other at a constant level, or at a usually smaller level with occasional larger values (“jackpots”) so the average reward was the same. Participants’ bias manifested when one option was consistently chosen with a higher level of accuracy, faster response time (RT) or a higher proportion of responses compared to the other available option (Vickers & Lee, 1998). We attempted to bias participants toward the colour with the higher potential payoff to initially test the effects of bias in decision-making, and additionally we manipulated the type of reward and schedule of delivery. We compared bias levels across four distinct reward conditions each with varying levels of reward salience and utility.

Initially this paper introduces theory explaining how decision outcomes can be altered using different incentives and schedules of reinforcement, focusing on which variables may alter bias most effectively. We review previous studies which investigated bias in two-choice decision-making and finally outline the present study. We then report outcomes of our experimental analyses, including the effect of rewards and prior information on bias. Separate analysis of cohort and individual means provide an indication of individual differences in bias. We focus primarily on testing the effect of different reward types and reward schedules on bias.

Bias as a resource-saving pattern of cognition

Use of heuristics is almost always the most adaptive way to make a decision, because although the ideal decision outcome is not guaranteed, much expenditure of time and computational effort is eliminated, resulting in a minimal net loss of resources (Simon, 1972). The concept of bounded rationality says that because resources such as time and computational power are always limited, decisions are often made through use of cognitive shortcuts. People often “satisfice” instead of “maximising”, meaning that they choose a “good enough” option rather than expending additional resources to identify the best outcome (Simon, 1972). Simon provides the example of a chess player with two options when considering each move: (1) the outcome of every possible move is calculated each time the player has a turn and the best option is implemented, maximising the probability of winning the game, or (2) a long-term strategy is applied, and players employ biases to satisfice and reduce the computational power required to choose which move to make. Simon explains that if infinite time and computational power were available, the first option will always yield the best outcome. However, resources are limited, so chess players instead examine a fraction of the available options and satisfice by choosing a move they consider to be “good enough” which fits with their overall strategy.

Investigating bias in decision-making

Ensuring that contextual factors such as rewards have a reliable and consistent influence on bias is key to accurate and robust research. This can be most easily achieved when research is conducted in a controlled experimental environment. It is particularly important to control extraneous variables when investigating bias in decision-making because decision outcomes are contextually bound, meaning that they change according to contextual factors such as external and internal influences, past experiences and prior knowledge (Tversky & Kahneman, 1974). External factors that can alter bias include the presence of rewards or punishments, and internal factors include individual differences such as subjective value of rewards, personal preference, prior information and experience

(Kable & Glimcher, 2007; Tversky & Kahneman, 1974). For example, Jonas, Schulz-Hardt, Frey, and Thelen (2001) found that bias changed according to the mode of information presentation: participants demonstrated higher levels of confirmation bias when prior information was presented simultaneously rather than sequentially.

Controlling contextual factors while researching bias in decision-making can be done by using a computer program to generate stimuli and take measurements. This ensures consistency across participants by reducing experimenter effects and increases the accuracy and precision of data collection to allow high-powered statistical analysis of results. Computer-based testing also provides additional advantages of low cost, fast administration, and ease of detecting malingering (Zygouris & Tsolaki, 2015).

A collection of decision outcomes from one individual can be analysed to yield an indicator of bias levels through use measures such as reaction time, accuracy, and proportion of bias congruent responses. This provides a tangible manifestation of the latent cognitive processes that occur while a person makes a decision (Mulder, Wagenmakers, Ratcliff, Boekel, and Forstmann, 2012). Additional to these classic measures of cognitive bias, researchers have imaged brains under multiple bias manipulations and identified key areas throughout the frontoparietal region which are utilised during the decision-making process. As a result, bias in decision-making can be linked to specific regions of the brain (Heekeren et al., 2004; Mulder et al., 2012). Individual deviation from cohort norms may therefore be indicative specifically of frontoparietal region differences in the brain. In this way, understanding the factors which influence cognitive bias may help inform the future development of cognitive clinical assessments. Heathcote, Holloway, and Sauer

(2019) and Mulder et al. (2012) have both studied bias in visual discrimination tasks in a computerised context, each with findings indicating strong avenues for future research.

Heathcote et al. (2019) used a computerised colour discrimination task to observe the effects of expectation and rewards on bias in binary decisions (decisions with two options). Participants were asked to identify which colour was in majority in a two-colour visual stimulus which randomised regularly so that it appeared to be flashing. Researchers attempted to induce bias by rewarding correct responses with virtual in-game points in a 3:1 ratio: 300 points for correctly choosing option A, or 100 points for correctly choosing option B. Each of option A and B were correct in half of these trials. Researchers hypothesised that participants would be biased towards option A as a result of the higher payoff. Expectation bias was manipulated by informing participants prior to beginning the same colour discrimination task that option A would be correct three times more often than option B (i.e., 75% vs. 25%). Researchers hypothesised that participants would be biased toward option A as a result of being informed of the increased incidence of correct cases. Heathcote et al. found that both rewards and prior information had a significant influence on bias, however providing proportion information prior to beginning the task had a three times larger effect on bias compared to rewards. Heathcote et al. also noted that there were large individual differences on bias scores across all conditions, with the largest differences occurring in the reward condition. Heathcote et al. suggested that further research should be undertaken in a similar setting to understand the effects of rewards on bias and to investigate the large individual differences observed.

Mulder et al. (2012) also studied bias in a binary perceptual decision-making task using an arrow congruence task. Participants were shown an initial cue arrow and subsequently shown stimulus arrows, then asked to indicate whether the stimulus and cue arrows were pointing in the same or different directions. Mulder et al. compared levels of bias due to rewards and prior proportion information according to average accuracy and reaction times. To observe the effect of expectation bias due to prior information, participants were informed that option A would be the correct response in 80% of trials, while option B would be correct in 20% of trials. Mulder et al. also tested the effect of rewards on bias by awarding participants eight points for correct responses on option A, two points for correctly choosing option B, and no points for incorrect responses. Each of the two options were correct 50% of the time when points were being awarded. Mulder et al. hypothesised that participants would be biased toward option A in both the reward and prior information conditions. Participants completed the reward and prior information conditions both inside and outside an MRI scanner to observe which location in the brain was active when these bias-inducing tasks were undertaken. Mulder et al. found that participants were biased toward both the most likely option and the option providing larger rewards, though the prior information condition had a larger and more consistent effect on bias than rewards.

Mulder et al. (2012) suggested that the effect of rewards on bias may not have been as large as expected as a result of participants' motivation to be correct rather than to collect rewards. Participants were informed prior to beginning the task that they would gain an additional payoff of 10 euros if they performed perfectly, thus placing greater emphasis on the need to be correct than to gather points. If participants were motivated to gain the extra remuneration, these instructions may have influenced overall bias in both conditions, as this additional reward may have interacted with the points awarded for individual correct responses.

Research from Mulder et al. (2012) and Heathcote et al. (2019) indicate that rewards in a computerised context influence bias in binary decision-making. However, this effect has not yet been found to be consistent across participants and contexts. Using the foundation laid by Mulder et al. and Heathcote et al., the current research aims to further investigate the effects of bias due to rewards in two-choice perceptual discrimination tasks.

Mechanisms which alter bias

It is well established that rewards have a strong influence on behaviour, known simply as reinforcement learning (Skinner, 1958). However, in the context of binary perceptual decisions, research by Mulder et al. (2012) and Heathcote et al. (2019) indicate that virtual points have an inconsistent effect on bias in decision making across participants, which is also a relatively small effect in light of the evidence indicating rewards alter behaviour radically. Virtual points are seen to incentivise behaviour towards a certain outcome in many contexts including computerised games, board games, and team and individual sports (Claus & Boutilier, 1998; Ghory, 2004). Findings by Heathcote et al. and Mulder et al. may be explained by two key theories: (1) participants were failing to attend to their reward systems, and (2) participants did not perceive their rewards to have a high utility (Isen, Nygren, & Ashby, 1988). It is important to note that salience and utility are not independent of one another: when reward utility increases, attention to rewards also increases. For example, Zink et al. (2004) demonstrated that rewards have the greatest effect on behaviour when salience is accompanied by pleasurable emotions elicited by the reward (i.e., the effect of high subjective utility).

Reward salience, or attention to rewards, has been shown by Libera and Chelazzi (2006) to be an integral part of behaviour change elicited by reinforcement.

Salience is a broad umbrella term which encompasses many factors. In the context of a computerised decision-making task, salience could be altered by factors such as reward size, type, and delivery mechanism (Hull, Williams, & Griffiths, 2013). For example, reward salience is likely to increase when rewards are delivered in a variable ratio schedule rather than being delivered constantly (Dertwinkel-Kalty & Köster, 2018). Variable ratio schedules of reinforcement occur when rewards are delivered randomly within predetermined fixed bounds and are most commonly seen in the form of jackpots in gambling-like games. Providing rewards within a variable ratio schedule is known to produce robust learning effects, making this method a powerful tool to alter behaviour (Rachlin, 1990).

Increasing subjective utility of rewards within a similar experimental setting to that of Mulder et al. (2012) and Heathcote et al. (2019) could be achieved by replacing virtual points with valid currency that participants redeem at the end of their session (Etzel, Cole, Zacks, Kay, & Braver, 2015; Kable & Glimcher, 2007; Pessiglione et al., 2007). If the perceived utility of rewards was increased, reward salience is also likely to increase (Zink et al., 2004). A combination of money and variable ratio reward schedules makes use of the same principles commonly seen in gambling activities and is likely to increase salience and attendance to rewards markedly (Ferster & Skinner, 1957; James, O'Malley, & Tunney, 2017). In the current research we combine the effects of increased reward salience and utility with the aim of producing a strong effect of bias due to rewards in decision-making.

Measuring bias in decision-making

Common measures of bias include accuracy, response time (RT), and bias congruence (the proportion of responses which align with the option that researchers attempted to bias them toward) (Ratcliff, Smith, & McKoon, 2015). Higher bias is indicated by responses made with higher accuracy, smaller RT (i.e., faster), or a larger proportion of bias congruent responses (Vickers & Lee, 1998). It is important to note that accuracy and response time are inversely related, known as the speed-accuracy trade-off, wherein faster responses tend to be less accurate, and slower responses are more accurate (Wickelgren, 1977). Because of the relationship between RT and accuracy, many researchers opt to measure only one of these variables. In the present study we measured both accuracy and RT and analysed them independently to gain a rigorous understanding of the effect of rewards on bias according to multiple dependent measures. However, interpretation of overall results patterns must be made with the knowledge of this inverse relationship between RT and accuracy.

The present research

We investigated the effect of rewards on bias in a two-choice perceptual discrimination task in a computerised context. We extended on research by Heathcote et al. (2019) and Mulder et al. (2012) by manipulating both the type and delivery schedule of rewards to examine the effect of increased reward salience and utility on bias in decision-making.

Although punishment (i.e., the addition of something negative, or the removal of something positive) has been shown to influence bias, we opted to omit a punishment condition from the current research for simplicity. We later discuss the potential effect of punishment on bias in the discussion section of this paper.

For design simplicity, we analytically controlled for individual differences in bias and measured and reported outcomes, rather than conducting inferential analyses to draw causal conclusions. Though increasing reward salience and utility may produce a more uniform effect of bias in decision-making, the primary aim of the current research was to understand the effect of rewards on bias, rather than to understand the cause of individual differences in bias. Therefore, we limited our analysis of individual differences to provide only a basis for future research by graphing and analysing individual participants' means as well as cohort averages, as done previously by Heathcote et al. (2019).

Each participant was assigned either orange or blue as their "bias-for" colour. We attempted to bias participants toward choosing this colour more frequently, with greater accuracy, or more quickly than their "bias-against" colour. To achieve this, we provided larger rewards, either at a constant level or with irregular jackpots for correct responses to stimuli with the bias-for colour in majority. Correct responses on the other colour (i.e., bias-against colour) still received rewards, though their expected value was smaller.

Stimuli and responses were binary, meaning that each had only two possible outcomes: bias congruent or bias incongruent. Bias congruent stimuli are defined as those with a participant's bias-for colour in majority (i.e., the colour that provided larger rewards), and vice versa for bias incongruent stimuli. Bias congruent responses occurred when participants chose to their bias-for colour as a decision response, regardless of whether they were correct. Similarly, bias incongruent responses occurred when participants responded with their bias-against colour, regardless of whether they were correct.

All participants completed five conditions: four reward conditions and a prior information condition. The four reward conditions were constructed from a 2 (Reward Schedule: constant, variable (i.e., jackpots)) x 2 (Reward Type: money, virtual points) design, to yield: (a) jackpot money; (b) jackpot points; (c) constant money; and (d) constant points.

The jackpot conditions (a and b) delivered rewards in a variable ratio schedule of reinforcement for correct bias congruent responses. Participants gained 100 points or tokens for every correct response and had the opportunity to gain an extra 1000 points or tokens (total 1100) every fifth time a bias congruent stimulus was presented (on average every tenth trial, as bias congruent and bias incongruent trials occurred half of the time each). The constant conditions (c and d) delivered 300 points or tokens for correct responses to bias congruent stimuli, and 100 points or tokens for correct responses to bias incongruent stimuli. Bias congruent and bias incongruent stimuli occurred equally often in the four reward conditions (i.e., 50% bias congruent stimuli and 50% bias incongruent stimuli) in order to observe bias as a manifestation of reward rate and reward type, independent of the frequency of bias congruent or bias incongruent stimuli.

Monetary rewards and virtual points were awarded in the same quantities but were represented on-screen as a money bag symbol and a swirl symbol, respectively. At the conclusion of participation, money was sent as a gift card with value according to participants' final cumulative score for trials offering monetary rewards.

The prior information condition was used as a benchmark against which to compare the four reward conditions and assess their success. Previous studies investigating bias in decision-making found that providing a priori information on the likelihood of each option being correct produces large, significant changes in bias, while the reward conditions produced more varied results (Heathcote et al., 2019; Mulder et al., 2012). Before beginning the prior information condition, participants were told that 75% of trials would have bias congruent stimuli and 25% of trials would have bias incongruent stimuli. Participants did not receive points or money for trials in the prior information condition, but instead were given feedback as to whether they were right or wrong.

The extent of participants' bias was measured by three outcome variables: (a) response time (RT), the time from stimulus onset to participant response; (b) accuracy, the proportion of correct trials; (c) bias congruence, the proportion of bias congruent responses out of all responses. Higher levels of bias were indicated by faster response times, higher accuracy, and more bias congruent responses.

Hypotheses

Hypothesis 1: Given previous literature indicating a strong effect of money on behaviour (Etzel et al., 2015; Pessiglione et al., 2007), we hypothesised that participants would respond with greater bias (i.e., higher accuracy, faster RT, and more bias congruent responses) for all bias congruent stimuli in the two conditions rewarded with money compared to the two conditions rewarded with points, regardless of reward schedule.

Hypothesis 2: Previous studies have shown the strong effect of variable ratio schedules of reinforcement on behaviour change (Skinner, 1958). As a result, we hypothesised that participants would respond with greater bias for all bias congruent stimuli in the two jackpotting conditions compared to the two constant conditions, regardless of reward type.

Hypothesis 3: Based on previous literature addressing rewards and schedules of reinforcement (James, O'Malley, & Tunney, 2017), we hypothesised that participants would responds with greatest bias for all bias congruent stimuli in the reward condition called jackpot money, compared to the other three reward conditions (jackpot points, constant money, constant points).

Hypothesis 4: Studies have indicated a consistent effect of prior information on bias, and a smaller, variable effect of rewards on bias (Mulder et al., 2012; Heathcote et al., 2019). As a result, we hypothesised that participants would respond with greater bias for all bias congruent stimuli in the prior information condition compared to the four reward conditions.

Method

Design

The current study used a 2 (Reward Type: points or money) x 2 (Reward Schedule: constant or variable) fully within-subjects design where each participant saw an equal number of majority-blue and majority-orange stimuli. There was an additional within-subjects condition that manipulated the proportion of occurrences of each stimulus, but these trials were not rewarded. This prior information condition is known to be effective in producing bias effects and was used as a comparison to evaluate the magnitude of bias effects in the reward condition.

Counterbalancing was undertaken to reduce carryover effects. The following five variables were counterbalanced, resulting in 32 unique sequences of experimental conditions (Appendix E): Reward Schedule between each session (constant or variable), Reward Type within each session (points or money), condition (reward or prior information), bias-for colour (blue or orange) and bias-for colour response key (z or / keys). Reward schedule was split by session to reduce participant confusion, so that participants completed only trials with a variable ratio or a constant reward schedule on any one day. Participants were randomly allocated to the 32 counterbalance groups. All participants completed 280 test trials in each of the five conditions (constant points, constant money, jackpot points, jackpot money, and prior information).

Participants

We recruited 35 participants who each completed all five experimental conditions. After data screening (see Results section for details), data from 32 participants was included in the final dataset, totaling one full counterbalance. Of the data used for analysis, participants were aged between 18 and 41 (M = 24.66, SD = 6.18), of which 19 were female and 13 were male. Participants were recruited through the online University of Tasmania psychology research participation system (SONA) and through flyers placed around the Sandy Bay campus of the University of Tasmania.

After completing both gameplay sessions, each participant's total number of accumulated tokens out of the number of obtainable tokens was calculated. Participants were provided a corresponding proportion of $15 AUD as a reward for performance in the two monetary reward conditions (jackpot money and constant money). Reward money was provided in the form of a Coles-Myer group gift card sent via email. All participants received at least $10 AUD but were not informed this until after competition of both gameplay sessions, though only one participant did not surpass this threshold through their own efforts. First year undergraduate psychology students (n = 23) received two hours of research course credit additional to their gift voucher.

The present research was approved by the Tasmanian Social Sciences Human Research Ethics Committee at the University of Tasmania on May 17, 2019 (Appendix A). The ethics approval reference number for this research is H0018111.

Stimuli

Participants were presented with a grid of blue and orange coloured squares and were asked to indicate which colour was in majority. For all trials, the grid was filled with 52% of one colour (correct response) and 48% of the other (incorrect response). To prevent participants from counting, the position of each square randomly updated 20 times per second, resulting in a stimulus that appeared to be scrambling and flashing.

The stimuli were imbedded in a computerised game called *Ari's Staff,* as shown in *Figure 1*. This game was developed by Matthew Gretton at the Tasmanian Cognition Laboratory, University of Tasmania. Participants were told that in order to break down the door and progress to the next level, Ari needed to cast the correct coloured spell (the colour in majority in the stimulus) at the door.

Ari's Staff was developed through the Unity game engine (version 2018.3.8f1). Participants played *Ari's Staff* on PCs running Windows 10 with 24" monitors, 1920x1080 resolution and a capacity for 60 frames per second. The coloured grid stimulus was approximately 52x57 squares, which corresponded to approximately 130x142mm on the computer monitor.

Figure 1. Screenshot of *Ari's Staff*.

Procedure

Participants were asked to read the Participant Information Sheet (Appendix B) which details risks and potential outcomes of the current study. Participants were asked to give written informed consent to participate by signing the Participant Consent Form (Appendix C), which included consent for deidentified data to be published on the Open Science Framework for review and potential further use by other researchers.

Participants played *Ari's Staff* on separate PCs in a room of no more than four total participants at the Tasmanian Cognition Laboratory at the Sandy Bay campus of the University of Tasmania. Participants played *Ari's Staff* for two one-hour sessions on different days no more than 14 days apart. Neutral-coloured screens were placed either side of participants' computer cubicles to reduce the effects of distraction.

Participants were provided with a colour-printed copy of the General Instruction Sheet (Appendix D) to refer to while playing *Ari's Staff*. Participants were also prompted by on-screen instructions detailing how to play (Appendix F) with specific directives separating money vs. virtual points as rewards, and constant vs. variable reward schedules.

Regardless of participant success rate, each block of trials ended when participants had completed 140 test trials of three seconds each (two seconds from the onset of the stimulus to the participant's response, and one second for immediate on-screen feedback). Each block of 140 trials was completed in approximately seven minutes. Each block ended with an on-screen prompt for participants to take a break, alongside instructions for the next block of trials and an option to continue when ready. Participants completed five blocks per session and chose the length of breaks between blocks, proceeding to the next block when they were ready. Participants completed 20 practice trials immediately before test trials of each constant, jackpotting and prior information conditions (but we did not provide practice trials when blocks changed from money to points). Each participant completed 280 test trials for each of the five conditions, making a total of 8,960 test trials for each of the five experimental conditions (four reward conditions and one prior proportion information condition).

Manipulations

Reward conditions. In the four reward conditions, stimuli had more blue squares in 50% of trials and more orange squares in the other 50%. Participants were informed of this equal distribution prior to beginning the task. After being presented with the stimulus and selecting which colour they believed to be in majority, participants were provided with immediate feedback as to whether the colour chosen was truly in majority (correct) or not (incorrect). This feedback included the number of points or tokens received, which were displayed immediately after participants' colour choice was made. Participants' accumulating total points or tokens for each block were displayed in the top righthand corner of the computer screen. The expected value in all reward conditions was 300 points or tokens for bias-for trials and 100 points or tokens for bias-against trials. Participants were allocated zero points or tokens for incorrect responses.

In the constant points and constant money conditions, rewards were in a 3:1 ratio, such that when participants correctly chose the bias-for colour they were rewarded with 300 points or tokens, and correct responses on the bias-against colour were rewarded with 100 points or tokens. In the jackpot points and jackpot money conditions, baseline rewards were in a 1:1 ratio, such that correct responses of either colour were rewarded with 100 points or tokens.

Jackpotting occurred in 20% of trials with the bias-for colour in majority yielding an opportunity to gain an additional 1000 tokens or points if the correct colour was chosen (total reward of 1100 tokens or points for a correct response when a jackpot opportunity was present). Participants were not informed of the presence of a jackpot opportunity unless they responded correctly when one was presented. That is, they were not told beforehand that the extra 1000 points or tokens were available, and nor were they told afterwards that they had missed the extra rewards if they responded incorrectly. When correct responses were made to a stimulus presenting a jackpot opportunity, participants were given immediate feedback with the additional 1000 points or tokens awarded.

Prior information condition. The prior proportion information condition was fundamentally different from the reward conditions in that 75% of trials displayed a stimulus with the bias-for colour in majority, and 25% of trials displayed a stimulus with the bias-against colour in majority. Participants were informed of these statistics before they began. No points or tokens were awarded in the prior information condition, however feedback ("correct" or "incorrect") was presented on-screen immediately after a response was chosen.

Results

Data screening

All practice trials and anticipatory responses (RT < .25s) were excluded from the dataset (Jain, Bansal, Kumar, & Singh, 2015). All participants had less than 7% anticipatory responses (*M* = 0.36%, *SD* = 1.22%), and a maximum of 4% non-responses (*M* = 0.51%, *SD* = 0.68%).

Three participants' data were excluded: two duplicate counterbalance sequences (one due to an experimenter's error and the other a participant dropped out and re-engaged after their counterbalance sequence had been replaced) and one participant had RTs truncated toward the two-second time cut-off. Including extra counterbalance sequences in the final dataset for some sequences and not others contradicts the initial motivation for counterbalancing, thus they were excluded. The dataset with truncated RTs was re-collected from a newly recruited participant.

Analysis

We used generalised linear mixed effects models (GLMMs) and linear mixed effects models (LMEs) to analyse our data. All analyses were completed in the 2019 version of the open-source statistical software R using the lme4 package to initially compute GLMMs and LME models (Bates, Maechler, Bolker, & Walker, 2015), and corresponding ANOVAs or t-tests were calculated using the car package (Fox & Weisberg, 2019). We analysed the factor "participants" as a random variable, which allowed intercepts to be random rather than fixed, thus including the variation between participants in the analysis, rather than wrongly assuming that all participants responded uniformly (Baayen, Davidson, & Bates, 2008).

GLMMs were used to analyse accuracy (proportion of correct responses) and bias congruence (proportion of bias congruent responses) using a binomial error model with the probit link function. The binomial error model was used to account for the binomial distribution due to binary response outcomes (e.g., orange or blue), with the probit link function to convert probabilities of response outcomes to a continuous scale for analysis. See Parzen et al. (2011) and Caffo and Griswold (2006) for reviews of this method.

LME models were used to analyse the logarithm of response time (RT; the time from stimulus display to participant response measured in seconds). We transformed RT data from a positively skewed distribution with skewness of 1.36 and kurtosis of 2.23 to a more normal distribution with skewness of 0.49 and kurtosis of 0.27 by applying a logarithmic transformation to all datapoints. Means were calculated after applying the logarithm transformation so that they corresponded to the inferential analysis. Later we transformed means back to the natural scale to aid interpretation.

Appropriate effect size calculation for mixed effects models (i.e., GLMMs and LME models) continue to be debated among academics and mathematicians, as multi-level models have multiple levels of variance which could be used to calculate an effect size (Jaeger, Edwards, Das, & Sen, 2017). Instead of reporting a classic inferential effect size, we report proportions for both accuracy and proportion of bias congruent responses, and seconds for reaction time. This allows simple and comprehensible illustrations of the magnitude of an effect (Pek & Flora, 2018).

Accuracy and reaction time were analysed according to four predictor variables: stimulus congruence (true or false; within subjects), bias-for colour (orange or blue; between subjects), Reward Schedule (variable or constant; within subjects) and Reward Type (money or points; within subjects). Bias congruence was analysed according to the same four predictor variables but excluding stimulus congruence, as this analysis is confounded with accuracy.

We define a bias congruent response as any occasion when participants chose their bias-for colour (the colour which provided on average higher rewards for correct responses), regardless of whether their response was correct. Similarly, bias incongruent responses are defined as occasions where participants chose their bias-against colour, regardless of whether their response was correct. Bias congruent stimuli are defined as those which have the majority colour the same as the participant's overall bias-for colour.

In the analyses following, participants are considered biased towards one option over the other when responses are on average faster, more accurate, or have a higher proportion of bias congruent responses. When interpreting model outputs according to accuracy and RT, the key factor to interpret is the interaction between stimulus congruence (S) and the other three manipulated factors: Reward Type (MP; money vs. points), Reward Schedule (CV; constant vs. variable), and overall bias-for colour (C). Comparing responses to bias congruent stimuli vs. bias incongruent stimuli reveals the difference in participants' bias between opportunities to gain a larger reward (300 vs. 100) or jackpot opportunity (1100 vs. 100). As per Hypotheses 1 and 2, we expected participants to exhibit greater bias toward bias congruent stimuli than bias incongruent stimuli.

We first outline results according to the three dependent measures (accuracy, RT, and probability of bias congruent responses), then explore individual differences across participants. Next, we examine the effect of bias-for colour on bias and finally compare the prior information condition to the reward conditions. Table 1 shows the output from a GLMM analysis of bias congruence. Table 2 shows outputs from a GLMM according to accuracy and an LME model according to RT. Means and detailed explanations of these results follow their respective tables in-text. All Standard Errors of the Mean for the following analyses were less than 0.10.

Bias according to proportion of bias congruent responses

Table 1

Chi-square and p-values for bias congruence (GLMM) analysis: Bias due to rewards

	Bias congruence	
Factor(s)	χ^2	p
Reward Type (MP)	0.73	.391
Reward Schedule (CV)	2.48	.116
Bias-for colour (C)	3.16	.075
MP:CV	0.01	.940
MP:C	3.45	.063
CV:C	0.23	.635
MP:CV:C	0.56	.440

Note: MP = Reward Type (Money, Points). CV = Reward Schedule (Constant, Variable). C = Bias-for colour (orange, blue). Interactions between factors are indicated by a colon separating their labels. Degrees of freedom = 1 for all comparisons.

We first analysed the effect of bias due to Reward Type and Reward Schedule according to participants' proportion of bias congruent responses. The overall probability of participants selecting a bias congruent response (0.54, 95% CI [0.54, 0.55]) was significantly greater than chance (i.e., 0.5) according to an exact binomial test, $p < .001$. There was no significant difference in bias congruence according to the factors Reward Type (money vs. points), Reward Schedule (constant vs. variable), and bias-for colour (blue vs. orange) in a three-way ANOVA.

Model comparison indicated that an intercept-only model (i.e., with no factor effects) was more appropriate than the three-way ANOVA, by measures of AIC (48897 vs. 48901) and clearly by BIC (48914 vs. 48977), with a non-significant decrease in deviance, χ^2 (7) = 10.50, p = .162.

Overall, this pattern of results suggests that there is an effect of bias, but that this effect is not modulated by either of the factors Reward Type or Reward Schedule as was expected (Hypotheses 1, 2 and 3).

Bias according to accuracy and reaction time

Table 2

Chi-square and p-values for accuracy (GLMM) and RT (LME) analyses: Bias due to rewards

	Reaction Time		Accuracy	
Factor(s)	χ^2	*p*	χ^2	*p*
MP	18.85	<.001***	1.73	.188
CV	60.45	<.001***	18.08	<.001***
S	575.40	<.001***	510.68	<.001***
C	0.12	.744	0.03	.859
MP:S	2.05	.152	1.08	.298
CV:S	2.88	.090	2.03	.155
C:S	3.78	.052	54.34	<.001***
MP:CV	10.33	.001**	0.07	.788
MP:C	4.14	.042*	1.57	.210
CV:C	22.78	<.001***	0.52	.472
MP:CV:S	1.57	.210	0.03	.869
MP:CV:C	1.88	.170	0.38	.537
MP:S:C	0.63	.429	5.66	.017*
CV:S:C	0.56	.455	0.38	.539
MP:CV:S:C	0.34	.560	1.13	.289

Note: MP = Reward Type (Money, Points). CV = Reward Schedule (Constant, Variable). S = Stimulus (bias congruent, bias incongruent). C = Bias-for colour (orange, blue). Interactions between factors are indicated by a colon separating their labels. Degrees of freedom = 1 for all comparisons. Significance codes: $p < .001$ ***; $p < .01$ **; $p < .05$ *.

When Reward Type and Reward Schedule were analysed according to accuracy and RT (indicated in Table 2 by MP:S, CV:S, and MP:CV:S), we expected participants to respond with significantly faster RTs and higher accuracy when presented with bias congruent stimuli compared to bias incongruent stimuli. We also expected to see higher levels of bias when participants were rewarded with money compared to points, and when rewarded in a jackpotting schedule compared to constantly (Hypotheses 1, 2 and 3).

Accuracy. We found a small effect of Reward Type on accuracy such that participants were more accurate on constant trials (84.2%) than jackpot trials (82.5%) and a much stronger effect with significantly greater accuracy for stimuli favoured by bias (87.8%) than not (78.9%), both with $p < .001$. This stimulus congruence effect interacted with participants bias-for colour, being larger for blue (11.7%) than orange (6.1%).

There was a significant three-way interaction between bias-for colour, Reward Type, and Stimulus: when stimuli were blue, participants were more accurate for money (12.2%) than points (11.2%) whereas there was a larger and opposite effect for orange (4.7% vs. 7.5% for money vs. points respectively). However, all methods of model comparison favoured a model that did not include Reward Type as a predictor and included only the main effect of Reward Schedule but no higher-order interactions.

When compared to a model with only bias-for colour and stimuli congruence as factors, the model with only the main effect of Reward Schedule and no terms with Reward Type was preferred by measures of AIC (30833 vs. 30816) and BIC (30875 vs. 30867). We also observed a significant decrease in model deviance, χ^2 (1) = 18.12, $p < .001$.

In summary, the analysis of accuracy supports an overall effect of bias, but not modulation of this effect by either Reward Type or Reward Schedule.

Reaction time. When log-RT was analysed according to Reward Type, there was a small, significant overall increase in RT for points (0.806s) compared to money (0.796s). Similarly, RT changed significantly due to Reward Schedule with participants reacting more slowly when rewarded in a variable ratio schedule (0.809s) than constantly (0.793s). We observed a large, significant decrease in RTs when stimuli favoured by bias were presented (0.775s) compared to bias incongruent stimuli (0.827s). Furthermore, Reward Schedule interacted with both Reward Type ($p < .001$) and bias-for colour ($p = .001$).

There were also two interactions in which participants favoured bias congruent stimuli over bias incongruent: there was a larger discrepancy between bias congruent and incongruent stimuli when bias-for colour was blue (0.056s) than orange (0.047s), and similarly there was a larger effect for variable (0.056s) than constant (0.048s).

We compared an initial model containing all significant ($p < .05$) terms to models with the terms approaching significance ($p < .09$) added one at a time, and then together. By the measure AIC the models with stimulus congruence included were preferred to the simpler model (3818 vs. 3820). The measure BIC (which penalises models which include more factors, as these models are more likely to fit the data by chance) indicated that the simpler model without stimulus congruence interactions provided a better tradeoff between model complexity and data fit than the more complex model (3905 vs. 3912).

We can see clear evidence that participants were biased according to RT, but little evidence that factors Reward Type and Reward Schedule were involved in this effect. At best, there is weak support for the bias effect on RT being a little larger when rewarded in a variable ratio schedule of reinforcement compared to constant rewards.

Overall for the analysis of RT and accuracy, there is clear evidence in the probability of bias congruent responses, levels of accuracy and speed of responses that the bias manipulation was effective, but that Reward Type and Reward Schedule had little or no significant influence on bias. In most cases, model selection indicated that Reward Type and Reward Schedule did not contribute to the bias effect we observed.

Individual differences

The figures below depict each participant's differences in bias levels between trials presenting rewards in a variable or constant schedule (Figure 2), and trials offering money or points as rewards (Figure 3).

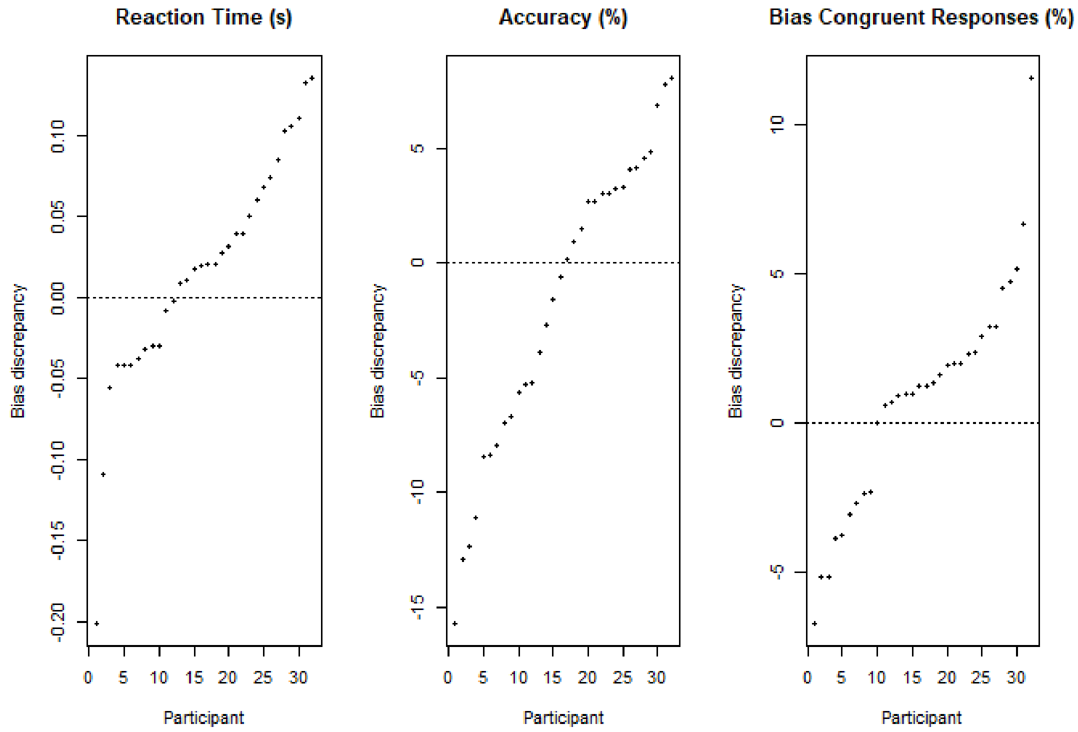

Figure 2. Individual bias discrepancies according to Reward Schedule for each of 32 participants. Differences between Jackpot and Constant conditions are ordered by magnitude. Note: Positive bias discrepancies indicate a larger bias when rewarded variably rather than constantly.

Figure 2 indicates a clear spread of bias discrepancy between participants, with a trend indicating higher bias when rewarded in a variable schedule compared to constantly according to RT and proportion of bias congruent responses, but more participants responding with higher accuracy for constant trials than jackpot.

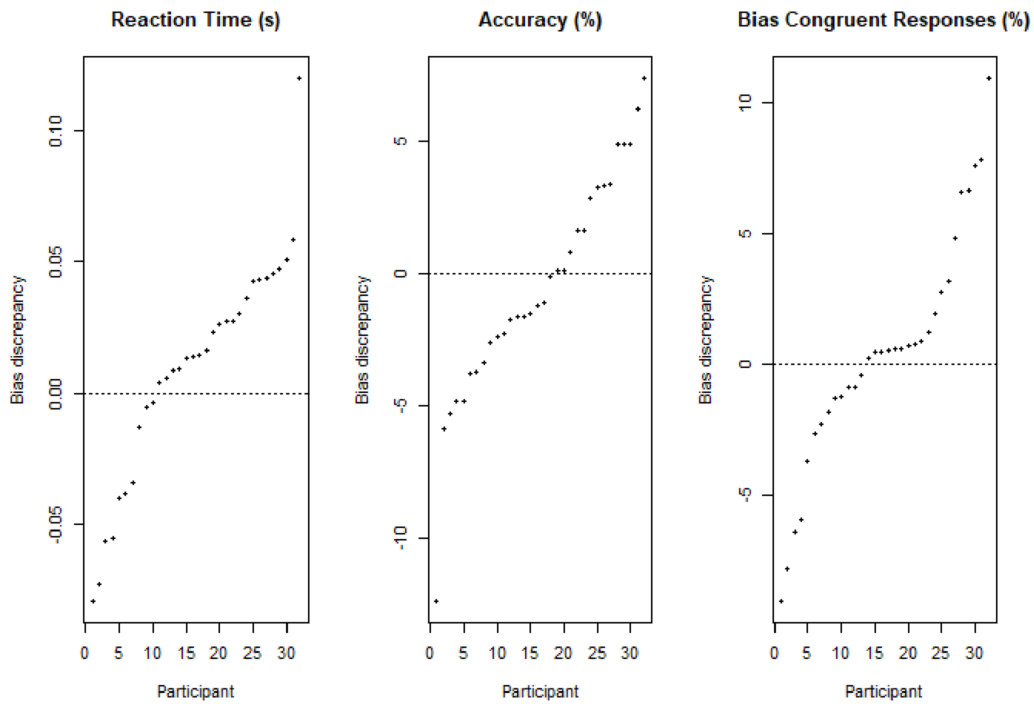

Figure 3. Individual bias discrepancies according to Reward Type for each of 32 participants. Differences between Money and Points conditions are ordered by magnitude. Note: Positive bias discrepancies indicate larger bias when rewarded with points than money.

Figure 3 depicts an almost uniform spread of bias discrepancies across participants according to Reward Type according to accuracy, however more participants were biased toward trials rewarding them with points over money according to RT and bias congruent responses.

Colour effects

When data was analysed according to proportion of bias congruent responses, the main effect of bias-for colour and the interaction between Reward Type and bias-for colour both approached significance (p = .063 and p = .075 respectively). Participants were biased toward money over points when blue was their bias-for colour (0.5%), but a larger, opposite effect was true when orange was their bias-for colour (1.4%).

There was no main effect of bias-for colour according to either RT or accuracy, but when split according to bias congruence of stimuli participants the effect of bias was stronger for blue than orange according to accuracy (11.7% vs. 6.1%) at the significance level $p < .001$. Similarly, this bias-for colour interaction with stimulus congruence approached significance ($p = .052$) when analysed according to RT with faster responses but a smaller effect for orange (0.047s) than blue (0.056s).

There was an interaction between bias-for colour and both Reward Type and Reward Schedule according to RT. Participants responded equally for jackpot trials but with a larger decrease in speed when rewarded with a constant schedule for orange (0.027s) than blue (0.006s). Participants were faster but experienced a smaller bias effect for orange (0.005s) than blue (0.014s).

Prior information vs. rewards

Given the negligible effect of the factors Reward Type and Reward Schedule on bias in the reward analysis, we analysed the bias effect of the prior information vs. reward conditions only according to two factors: stimulus congruence (congruent vs. incongruent) and condition (prior information vs. rewards). Additionally, we omitted bias congruence because this analysis is not valid when there is an unequal number of trials in each condition, as occurs in the prior information condition (i.e., trials are 75% majority bias-for colour and 25% majority bias-against colour, rather than 50% for each). We report and interpret the interaction between stimulus congruence and condition according to RT and accuracy to understand the difference in bias effects due to prior proportion vs. rewards.

There was a larger effect of bias according to RT when participants were rewarded (0.053s) compared to being provided prior information (0.043s), but this difference was not significant, χ^2 (1) = 2.4, p = .121. However, there was a clearly a much larger effect of bias according to accuracy for prior information (14.7%) than reward (8.9%), χ^2 (1) = 27.1, p < .001). When bias congruent stimuli were presented, there was little difference in accuracy for rewards (87.8%) and prior information (88.5%). When bias incongruent stimuli were presented, there was a larger drop in participants' accuracy for the prior information condition (73.7%) than the reward conditions (79.0%).

Discussion

The current research investigated the effects of rewards on bias in a binary colour- discrimination task. We attempted to induce bias in decision-making by providing larger rewards or a jackpot opportunity for one colour and not the other. Additionally, we rewarded some trials with points and others with money, comparing bias across these conditions.

The initial analysis which modelled predictors according to the probability of a bias congruent response indicated that participants chose to respond congruently with their bias-for colour more often than chance, however neither of the factors Reward Schedule nor Reward Type contributed heavily to this effect of bias. Similarly, analyses of RT and accuracy provided little to no evidence that bias changed according to money vs. points as the type of reward, or constant vs. variable as the reward schedule, and this was supported by model selection. We did not find evidence to support any of our novel hypotheses regarding an impact of rewards on bias (Hypotheses 1, 2 and 3). However, we found a stronger effect of bias in the prior information condition than the reward conditions (Hypothesis 4), providing further evidence in line with findings from Heathcote et al. (2019) and Mulder et al. (2012).

In light of previous literature, we can see no clear reasons why our manipulations did not have the intended effect on bias according to RT, accuracy, or proportion of bias congruent responses. Despite this, we identify possible driving mechanisms behind our findings. Finally, we discuss limitations of the current study and potential avenues for further research.

Reward Type

We expected participants would respond with greater bias when rewarded with money than points (Hypothesis 1). Much literature indicates that money activates reward pathways in the brain (Etzel et al., 2015; Pessiglione et al., 2007) and that people consider money to have a high utility (Johnson et al., 2018). However, our analyses provide clear evidence that Reward Type did not contribute to the observed bias effect.

Reward size is positively correlated with increased enjoyment and arousal, especially in a gaming context (Johnson et al., 2018; Lyons, 2015). Our finding that decision outcomes did not differ between money and points as rewards may have been due to the size of rewards more so than the type of reward. Rewarding participants with a maximum of $15 AUD across two one-hour sessions of gameplay may not have been large enough to elicit a difference in utility between money and virtual points in this context. However, this seems unlikely as monetary remuneration of a similar size has previously been successful in similar experimental designs (Grady, Dickert, Jawetz, Gensler, & Emanuel, 2005).

Providing course credits to 23 of 32 participants additional to their monetary payoff may have weakened the effect of our Reward Type manipulation. Research by Sharp, Pelletier, and Lévesque (2006) indicates that course credits can act as a strong reward which motivates attention and engagement, potentially more so than money or virtual points. Replication of the current research to include course credits as part of an experimental condition will clarify the effect of different types of rewards on bias.

Reward Schedule

The use of a variable ratio schedule of reinforcement to elicit greater bias compared to a constant schedule was used on the premise of ample previous research (Skinner, 1958), but despite this, our analyses provided minimal evidence in support of a difference in bias between a constant vs. variable reward schedule (Hypothesis 2).

Variable ratio reward systems are known to induce large and robust changes in behaviour however these can sometimes take time to develop (Skinner, 1958). We limited gameplay time to one hour per day to ensure participants did not become fatigued, however this also restricted time available for participants to become familiar with reinforcement schedules. It is possible that participants did not have enough time to understand and learn how to best respond while being rewarded in a variable schedule.

Furthermore, the frequency of jackpot occurrences may have been too low to elicit behaviour change in the current context. On average, jackpots occurred one in every ten trials, though participants were only aware of them when they responded correctly to stimuli. Previous research has shown that the success of variable ratio schedules of reinforcement is dependent on task context (Reed, 1992). Within the current context, jackpot reinforcements may not have occurred frequently enough to elicit behaviour change, though this seems doubtful in light of ample research indicating that reinforcements occurring every tenth, or even as infrequent as one in 50 spins on a slot machine, are enough to see a change in behaviour (Haw, 2008).

Fundamentally, Reward Schedule and Reward Type are dependent on one another: for a participant to receive a reward, an aspect of both factors must be employed (i.e., the presence of a reward is not enough, it must also be delivered in some schedule). Therefore, the effect of Reward Schedule may have been minimal for the same reasons that we did not observe a difference in bias according to Reward Type.

Prior information vs. rewards

We found strong evidence to indicate that the prior information condition produced larger effects on bias than the reward conditions, in support of Hypothesis 4. We found a larger effect of bias according to accuracy in the prior information condition compared to the reward conditions, though not according to RT. This fits into the speed-accuracy trade-off framework which we expected to occur as a result the known inverse relationship between RT and accuracy in decision-making (Wickelgren, 1977). Our findings provide further evidence to confirm results from Heathcote et al. (2019) and Mulder et al. (2012) that providing a priori proportion information elicits a greater level of bias in decision-making than rewarding correct responses.

The interaction between condition (reward vs. prior information) and stimulus congruence showed negligible differences in accuracy between conditions when stimuli were bias congruent, but a larger drop larger drop in accuracy for the prior proportion condition than the reward condition when stimuli were bias incongruent. Vickers' (1979) accumulator model may be a useful framework through which to understand this observation.

Vickers' (1979) accumulator model assumes that when a binary decision is being made, the two options each have a defined threshold of excitation required to be surpassed for that option to be chosen. As evidence for each option accumulates, the two options “race” in parallel to their individual excitation thresholds. Within Vickers’ accumulator model, higher bias is represented by a smaller distance between the start-point and threshold of excitation for one option compared to another. That is, less evidence in favour of that option is required because it has been pre-determined to be the “better” choice.

Further analysis is required to confirm the applicability of Vickers’ (1979) accumulator model to our data. However, we can tentatively draw the conclusion that the evidence required for participants to choose the colour occurring 75% of the time in the prior proportion condition was lesser than evidence required to choose the colour with the higher payoff in the reward condition. Thus, providing a priori proportion information elicited greater bias in participants than rewarding correct responses.

Individual differences

As seen by both Heathcote et al. (2019) and Mulder et al. (2012), we identified large individual differences between participants’ bias responses. Participants bias levels varied by approximately 0.15s and 25% accuracy according to Reward Schedule, and approximately 0.10s and 10% accuracy for Reward Type. Multiple participants responded with greater bias for money than points, and multiple in the opposite direction; a similar observation was made with constant vs. variable schedules of reinforcement. The speed-accuracy trade-off was apparent in the analysis of Reward Schedule, with more participants responding with larger bias according to RT for the jackpot conditions, but more participants with higher accuracy on the constant conditions.

The individual differences depicted in Figures 2 and 3 provide supporting evidence that defining “participants” as a random factor in multilevel modelling was appropriate. If participants were coded as a fixed factor, or not included in the analysis, the information shown in Figures 2 and 3 would have not been utilised in modelling. Instead, averages for each condition would have been taken, resulting in bias scores not reflective of the variation between participants. This is important because, as seen in Figures 2 and 3, multiple participants exhibit bias in opposite directions across both Reward Type and Reward Schedule according to all three measures of bias. These differences would have been averaged and true effects on bias blurred when all participants’ scores were averaged for each condition before analysis. Thus, our models are likely to reflect true patterns in the data as a result of including participants as a random factor.

Colour effects

We found multiple unexpected significant (or approaching $p < .05$) effects of bias-for colour on bias. The most notable and highly significant of these colour effects was the larger effect of bias as measured by accuracy for blue (11.7%) than orange (6.1%).

We chose the colours blue and orange to comprise the stimulus because this ensured that the estimated 5-8% of the male population unable to discriminate between blue and green colour hues would still be eligible to participate (Curcio, Sloan, Kalina, & Hendrickson, 1990). Bias-for colour was a between-subjects manipulation in which half of participants were randomly allocated to blue, and half to orange. It is possible that with such a small cohort of participants (N = 32), these effects were due to a systematic error in the random allocation to bias-for colour. However, as colour effects emerged consistently across all measures of bias and with high levels of significance, it is likely that these reflect a true effect of bias-for colour on bias.

Research by Guilford and Smith (1959) indicates that colour can manifest bias according to personal preference, colour intensity, brightness and saturation. Participants were found to prefer brighter and more saturated colours, with males rating all colours slightly higher than females. Highest colour preferences occur for hues in the blue and green range across cohorts, with lowest preference for yellow, through these effects were small. The preference for blue and green over yellow may correspond to our finding of participants' greater bias when rewarded more highly for correct blue responses over orange. Sex differences may also predict individual bias differences.

Limitations of this research

This research received approximately $450 AUD of funding in total to provide participant remuneration. Providing participants with small monetary incentives may have limited our ability to detect an effect of Reward Type. Larger rewards have been shown to increase reward salience and utility, and therefore are more likely to induce bias in decision-making (Johnson et al., 2018).

The manipulation Reward Type may have been weakened as a result of providing credits in addition to monetary remuneration for the majority of participants (Sharp et al., 2006). In future research, inclusion of course credits as an experimental manipulation will help clarify whether the presence of course credits as a reward interacts with other rewards such as money and points.

Gamification of the colour discrimination task in the present research was done to increase participant engagement with the task, as shown in research by Buckley and Doyle (2016). However, the specific gamification applied in this study has not been directly compared to the same task in a non-gamified setting. Thus, all conclusions in the current research are limited by the assumption that gamification increases participant motivation and attention alone and does not interact with other factors.

Directions for future research

Use of random rather than true scoring in future research may encourage participants to use heuristics and biases more than in the current design. By informing participants that on some occasions blue is treated as correct even when orange is truly in majority, a more severe element of randomness is introduced. Ideally, this manipulation will encourage participants to try to gain rewards is through use of strategies such as heuristics and biases rather than through accuracy. So long as error rates are high enough (i.e., approximately 20-40% as in the current study) participants are unlikely to detect whether random scoring is present or not, thus it may be enough to only inform participants that random scoring is present. It may also be appropriate to replicate this research through actually employing random scoring, rather than just informing participants that random scoring is present.

Punishment is known to influence bias in decision-making (Tversky & Kahneman, 1974). For simplicity, we adopted a design in which participants were not punished for incorrect responses but instead received zero rewards. Regardless of findings from the present research, further studies investigating the effect of punishment on bias in decision making would be a valuable addition to the existing knowledge of influences on bias in visual discrimination tasks. Conducting research to investigate the influence of both rewards and punishments on bias in the given context would require careful design to ensure that the two factors remained isolated during testing, allowing causal attributions to be made.

Contributions of this research

The current research has contributed to the literature on bias in decision making through testing the effects of money vs. points as rewards, and constant vs. variable reward schedules on bias in a computerised binary colour discrimination task. This study provides further evidence supporting the larger effect of bias due to a priori proportion information compared to rewards. Distinct from previous research, we found that neither money vs. points nor variable vs. constant reward schedules elicit a difference in bias. Specifically, we found that rewarding participants up to $15 AUD for two hours of participation or providing jackpots every 10th trial at most does not alter reward salience or utility enough to elicit a difference in bias in the present context. Additionally, we identified a large, significant increase in accuracy for participants rewarded more highly for correct blue responses than those rewarded more highly for correct orange responses. This may have implications for further research using coloured visual discrimination tasks.

Conclusions

We aimed to understand the effect of increasing the utility and salience of rewards on bias in a two-colour discrimination task. From the current study, we can conclude that neither monetary incentives up to $15 AUD vs. virtual points, nor jackpots available on every 10th trial vs. constant rewards alter reward salience or utility enough to elicit a differential effect on bias in a computerised binary colour discrimination task. This provides a strong avenue for future research to manipulate and test the effect of reward size, frequency of jackpot occurrences, and the effect of true vs. random scoring on bias in the context of a computerised visual discrimination task.

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Appendix A

Ethics Approval Letter

UNIVERSITY of TASMANIA

20 May 2019

Professor Andrew Heathcote
C/- University of Tasmania

Sent via email

Dear Professor Heathcote

REF NO: H0018111
TITLE: Reward effects on bias in a binary decision-making task

We are pleased to advise that acting on a mandate from the Tasmania Social Sciences HREC, the Chair of the committee considered and approved the above project on 17 May 2019.

Please ensure that all investigators involved with this project have cited the approved versions of the documents listed within this letter and use only these versions in conducting this research project.

This approval constitutes ethical clearance by the Tasmania Social Sciences HREC. The decision and authority to commence the associated research may be dependent on factors beyond the remit of the ethics review process. For example, your research may need ethics clearance from other organisations or review by your research governance coordinator or Head of Department. It is your responsibility to find out if the approvals of other bodies or authorities are required. It is recommended that the proposed research should not commence until you have satisfied these requirements.

In accordance with the National Statement on Ethical Conduct in Human Research, it is the responsibility of institutions and researchers to be aware of both general and specific legal requirements, wherever relevant. If researchers are uncertain they should seek legal advice to confirm that their proposed research is in compliant with the relevant laws. University of Tasmania researchers may seek legal advice from Legal Services at the University.

All committees operating under the Human Research Ethics Committee (Tasmania) Network are registered and required to comply with the *National Statement on the Ethical Conduct in Human Research* (NHMRC 2007 updated 2018).

Therefore, the Chief Investigator's responsibility is to ensure that:

(1) All investigators are aware of the terms of approval, and that the research is conducted in compliance with the HREC approved protocol or project description.

(2) Modifications to the protocol do not proceed until **approval** is obtained in writing from the HREC. This includes, but is not limited to, amendments that:

Human Research Ethics Committee (Tasmania) Network
Research Ethics and Integrity Unit
Office of Research Services
Private Bag 1
Hobart Tasmania
7001
Australia
T +61 3 6226 6254
E ss.ethics@utas.edu.au
ABN 30 764 374 782 /CRICOS 00586B
utas.edu.au

UNIVERSITY of TASMANIA

(i) are proposed or undertaken in order to eliminate immediate risks to participants;
(ii) may increase the risks to participants;
(iii) significantly affect the conduct of the research; or
(iv) involve changes to investigator involvement with the project.

Please note that all requests for changes to approved documents must include a version number and date when submitted for review by the HREC.

(3) Reports are provided to the HREC on the progress of the research and any safety reports or monitoring requirements as indicated in NHMRC guidance. Researchers should notify the HREC immediately of any serious or unexpected adverse effects on participants.

(4) The HREC is informed as soon as possible of any new safety information, from other published or unpublished research, that may have an impact on the continued ethical acceptability of the research or that may indicate the need for modification of the project.

(5) All research participants must be provided with the current Participant Information Sheet and Consent Form, unless otherwise approved by the Committee.

(6) This study has approval for four years contingent upon annual review. A *Progress Report* is to be provided on the anniversary date of your approval. Your first report is due 17 May 2020**,** and you will be sent a courtesy reminder closer to this due date. Ethical approval for this project will lapse if a Progress Report is not submitted in the time frame provided

(7) A *Final Report* and a copy of the published material, either in full or abstract, must be provided at the end of the project.

(8) The HREC is advised of any complaints received or ethical issues that arise during the course of the project.

(9) The HREC is advised promptly of the emergence of circumstances where a court, law enforcement agency or regulator seeks to compel the release of findings or results. Researchers must develop a strategy for addressing this and seek advice from the HREC.

Should you have any queries please do not hesitate to contact me on (03) 6226 6254 or via email ss.ethics@utas.edu.au.

Yours sincerely

Jude Vienna-Hallam
Executive Officer I Social Sciences

Human Research Ethics Committee (Tasmania) Network
Research Ethics and Integrity Unit
Office of Research Services

Private Bag 1
Hobart Tasmania
7001
Australia

T +61 3 6226 6254
E ss.ethics@utas.edu.au
ABN 30 764 374 782 /CRICOS 00586B

utas.edu.au

Appendix B

Participant Consent Form

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School of Medicine

What influences decision making more: thinking you're right or getting paid?

PARTICIPANT CONSENT FORM

Research team *Prof Andrew Heathcote,* School of Psychology, University of Tasmania
Dr Jim Sauer, School of Psychology, University of Tasmania
Elise Jurasovic, Honours student, School of Psychology, University of Tasmania

Contact details andrew.heathcote@utas.edu.au
jim.sauer@utas.edu.au
elise.jurasovic@utas.edu.au

By signing below, I confirm that I have read and understood the information sheet and in particular:

- I understand that my involvement in this research will include playing a computer game for two one-hour sessions
- I understand that the research will include recording of my response times and accuracy of decisions
- I understand that participation involves the risk of fatigue, which can be reduced by taking breaks when prompted at the end of each 5-minute block of trials
- Any questions that I have asked have been answered to my satisfaction
- I understand that all study data will deidentified and then stored on the Open Science Framework for potential further research and review by other scientists

  ☐ *I agree that my study data can be used for this specific project*

  ☐ *I agree that my de-identified study data can be shared on the Open Science Framework and used for future research projects in the same general area of this research*

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- I understand that the results of the study will be published so that I cannot be identified as a participant
- I understand that my participation in this research is voluntary
- I understand that I am free to withdraw at any time, without explanation or penalty
- I understand that I will not be able to withdraw my data after completing the research as data will be collected anonymously
- I agree to participate in the study

Age: _____ Sex: _____ Email (to send your giftcard to): ________________________

Giftcard choice (please circle one):

Kmart Coles Officeworks Target

Name	
Signature	
Date	

Statement by Researcher

☐ I have explained the project and the implications of participation in it to this volunteer and I believe that the consent is informed and that he/she understands the implications of participation.

If the researcher has not had an opportunity to talk to participants prior to them participating, the following must be ticked.

☐ The participant has received the Information Sheet where my details have been provided so participants have had the opportunity to contact me prior to consenting to participate in this project.

Name	
Signature	
Date	

Appendix C

Participant Information Sheet

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Reward effects on bias in a binary decision-making task

PARTICIPANT INFORMATION SHEET

Research team

Prof Andrew Heathcote, School of Psychology, University of Tasmania
Dr Jim Sauer, School of Psychology, University of Tasmania
Elise Jurasovic, Honours student, School of Psychology, University of Tasmania

Contact details

andrew.heathcote@utas.edu.au
jim.sauer@utas.edu.au
elise.jurasovic@utas.edu.au

1. Invitation

You are invited to participate in a research study examining bias in decision making.

2. What is the purpose of this study?

This study aims to investigate the effects of rewards on bias in decision making.

3. How is the study being funded?

This study is being funded through the UTAS Psychology Honours Student Research Fund and through Andrew Heathcote's research funding

4. Why have I been invited to participate?

You are eligible to take part in this study because you are over 18 years old and have normal or corrected-to-normal vision.
Your participation is voluntary, and your choice to take part or not take part will not affect your grades.

5. What will I be asked to do?

You will be asked your date of birth and then complete two sessions of playing a computer game. Each session will be completed on a different day and will take approximately one hour to complete (two hours total).
You will be asked to play a game with four different reward conditions (jackpotting money, consistent money, jackpotting points, consistent points) and one proportion information condition. Your accuracy and response speed will be recorded.
The game involves choosing either majority blue or majority orange from a grid. In each session, the game is divided into 10 blocks of around 5 minutes each. You are encouraged to take breaks between the blocks before continuing.

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6. Are there any possible benefits from participation in this study?

You will receive research credit as compensation for your time and will receive additional monetary compensation according to performance, up to $15 across the two sessions.

This study will also advance our knowledge of the effects of rewards on decision making and contribute to baseline information for future diagnostic tools. For example, we may develop a computerised diagnostic tool which identifies abnormal changes in decision-making related to aging and cognitive decline.

7. Are there any possible risks from participation in this study?

- The main risk to participants from participation in this study is fatigue
- To reduce discomfort, the opportunity for a break will be presented to participants every 5 minutes. You are encouraged to walk around, use the bathroom, or have a drink.
- While you are completing the game, a researcher will be present in the room nearby if you have any questions or issues with the program

8. What if I change my mind during or after the study?

You are free to withdraw without consequence before September 2019. After this your data may have already been included in analysis and it will not be possible to remove it because it will have been deidentified.

9. What will happen to the data when this study is over?

- Storage of data
  - Data will be fully deidentified (there will be no way to link data to you)
  - After deidentification, raw data will be stored online in the Open Science Framework and will be accessible for researchers worldwide to access and use for further analyses
  - Once on the Open Science Framework, your data will remain accessible for the foreseeable future and will not be destroyed

- Your data will be kept private and inaccessible to anyone but the researchers listed above until it has been deidentified.

10. How will the results of the study be published?

All data in this study will be completely anonymous. Data will be discussed by researchers at the University of Tasmania and may be published to a scientific journal. If you wish to be notified on the results of this study, please feel free to contact us.

11. What if I have questions about this study?

If you have any queries, concerns or issues with this study, please feel free to contact us:

- *Elise Jurasovic* elise.jurasovic@utas.edu.au
- *Prof Andrew Heathcote* andrew.heathcote@utas.edu.au
- *Dr Jim Sauer* jim.sauer@utas.edu.au

UNIVERSITY of TASMANIA

FACULTY OF HEALTH

School of Medicine

This study has been approved by the Tasmania Health and Medical/Social Sciences Human Research Ethics Committee. If you have concerns or complaints about the conduct of this study, you can contact the Executive Officer of the HREC (Tasmania) Network on (03) 6226 6254 or email human.ethics@utas.edu.au / ss.ethics@utas.edu.au. The Executive Officer is the person nominated to receive complaints from research participants. You will need to quote H0018111.

12. How can I agree to be involved?

You can give consent by signing the form titled “Participant Consent Form”.

Thank you for your time

Appendix D

Ari's Staff General Instruction Sheet

Ari's Staff – General Instruction Sheet

This is what the main screen of the game looks like. You need to decide whether there is more blue or more orange in the grid within the archway. (In this example, you would press / for blue, or z for orange.)

There's a fixed number of trials within each set. This means that no matter how many choices are right (or wrong), the game will take **exactly the same amount of time.**

You only get tokens if you get the spell correct. The more tokens you collect, the more money you get afterwards.

Swirls mean "points", and money bags mean "tokens". **ONLY the points you collect on money bag trials get converted to money at the end.**

Unless you're told otherwise, half the time the grid will be majority blue, and half the time it will be majority orange.

In summary:

1. Getting more trials right won't make the game end faster
2. Getting more money bag trials right will earn you more money (up to $15)
3. Unless the instructions say otherwise, half of trials will be majority blue and half majority orange

It is important to read the instructions for each new section (they change!) and take advantage of the opportunity for a break.

Come and let me know when you're done. Thanks for your time!

Appendix E

Counterbalance sequence

Participant	*Session 1*			*Session 2*			*Bias-for colour*	*Bias-for hand*
1	CP	CM	P	JP	JM	P	O	L
2	CM	CP	P	JM	JP	P	O	L
3	P	CP	CM	P	JM	JP	O	L
4	P	CM	CP	P	JP	JM	O	L
5	JP	JM	P	CP	CM	P	O	L
6	JM	JP	P	CM	CP	P	O	L
7	P	JM	JP	P	CP	CM	O	L
8	P	JP	JM	P	CM	CP	O	L
9	CP	CM	P	JP	JM	P	O	R
10	CM	CP	P	JM	JP	P	O	R
11	P	CP	CM	P	JM	JP	O	R
12	P	CM	CP	P	JP	JM	O	R
13	JP	JM	P	CP	CM	P	O	R
14	JM	JP	P	CM	CP	P	O	R
15	P	JM	JP	P	CP	CM	O	R
16	P	JP	JM	P	CM	CP	O	R
17	CP	CM	P	JP	JM	P	B	L
18	CM	CP	P	JM	JP	P	B	L
19	P	CP	CM	P	JM	JP	B	L
20	P	CM	CP	P	JP	JM	B	L
21	JP	JM	P	CP	CM	P	B	L
22	JM	JP	P	CM	CP	P	B	L
23	P	JM	JP	P	CP	CM	B	L
24	P	JP	JM	P	CM	CP	B	L
25	CP	CM	P	JP	JM	P	B	R
26	CM	CP	P	JM	JP	P	B	R
27	P	CP	CM	P	JM	JP	B	R
28	P	CM	CP	P	JP	JM	B	R
29	JP	JM	P	CP	CM	P	B	R
30	JM	JP	P	CM	CP	P	B	R
31	P	JM	JP	P	CP	CM	B	R
32	P	JP	JM	P	CM	CP	B	R

Notes. CP = Constant Points (280 trials). CM = Constant Money (280 trials). JP = Jackpot Points (280 trials). JM = Jackpot Money (280 trials). P = Prior Information (140 trials). B = Blue. O = Orange. L = Left hand. R = Right hand.

Appendix F

On-screen instructions during gameplay of *Ari's Staff*

General practice

Your path through the dungeon has been blocked by a mysterious door! The door has a collection of orange and blue dots.

In order to break down the door, Ari needs to cast the correct spell!

If more of the dots are orange then press the z / ? key. If more of the dots are blue then press the z / ? key.

For correct spells, Ari earns tokens. For incorrect spells, Ari doesn't gain or lose any tokens.

This is a **PRACTICE TRIAL**. Try to get the hang of the controls!

Constant trials

In this trial, Ari collects tokens when the correct spell is cast.

For correct *bias for colour* spells, Ari can earn 300 tokens / points.

For correct *bias against colour* spells, Ari can earn 100 tokens / points.

Earn as many tokens as you can, and if you're not sure which spell to cast, choose the one which will give you the most tokens / points.

If more of the dots are orange then press the z / ? key. If more of the dots are blue then press the z / ? key.

This is a **PRACTICE TRIAL**. The points you score here **DO / DON'T COUNT TOWARDS YOUR FINAL SCORE.**

Jackpot trials

In this trial, Ari collects tokens when the correct spell is cast.

For correct *bias for colour* and *bias against colour* spells, Ari earns 100 tokens / points. For correct *bias for colour* spells, 20% of the time Ari can earn an **additional 1000 tokens / points**.

Earn as many tokens / points as you can. If you're not sure which spell to cast, choose the one which will give you the most tokens / points.

If more of the dots are orange then press the z / ? key. If more of the dots are blue then press the z / ? key.

This is a **PRACTICE / TEST TRIAL**. The points you gather **DO / DON'T COUNT TOWARDS YOUR FINAL SCORE.**

Prior information trials

In this trial, Ari needs to cast the correct spell to break down the door.

75% of the time the mysterious door will have more *bias for colour* dots, and 25% of the time there will be more *bias against colour* dots.

If you're not sure which spell to cast, choose the one that occurs most often.

If more of the dots are orange then press the z / ? key. If more of the dots are blue then press the z / ? key.

This is a **PRACTICE TRIAL / TEST TRIAL**. Try to get the hang of the controls! / Good luck!